Identification of Water Bodies from High and Multi-level Resolution Satellite Images Using Novel Feature Extracting Technique

Satellite Image Processing

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Abstract

Water bodies are precious resources which play an important role in agriculture, transportation, drinking water supply and environmental balance of ground water level and so on. Assessment on water-bodies as well as escribing on its characteristics is the most crucial work to be done in India where land is being occupied at a very high rate. Satellite images are not clear all the time and will have shadow effects, which has to identified and distinguished. Water body image may appear similar to shades of huge buildings due to reflection and echoing. Few substantial research have been conducted to extract information about water bodies from several multi-resolution satellite images. This paper proposes a novel methodology based on texture and spectral information of the satellite images to extract water bodies.

Keywords

Multi-resolution Satellite Image; Remote Sensing

Introduction

The proposed feature extraction methodology based on textural, spectral and contextual information is described. This methodology, expected to increase the accuracy of extracted single specified feature like water bodies, consists of four modules. Firstly, the best texture element from panchromatic image is extracted using Grey Level Co-occurrence Matrix in overlapping and non-overlapping modes. Secondly, fused textural and multispectral image will be classified using Maximum Likelihood classifier. Thirdly, Edge detector Canny will be applied to provide the contextual data. Finally, textural and contextual data will be given to Markovien Random Field filter to extract the feature. The result of the experiments conducted on IRS P6 LISS IV data is presented. The results of overlapping and non overlapping methods are compared.

Background Information

It is prominent that no earth observation satellites are orbiting our planet to provide rife imagery of its surface. The space borne sensors can be divided in the measuring reflection of sunlight into the visible and infrared part of the electromagnetic spectrum and thermal infrared radiance, and those actively transmitting microwave pulses and recording the received signal. Optical satellite systems are the most frequently applied in water body extraction research. The parts of the electromagnetic spectrum covered by these sensors include the visible and near infrared (VNIR) ranging from 0.4 to 1.3 μm, the shortwave infrared (SWIR) between 1.3 and 3.0 μm, the thermal infrared (TIR) from 3.0 to 15.0 μm and the long-wavelength infrared (LWIR) from (7-14 μm). Landsat is still among the widest used satellites, partly because it has the longest time series of data of currently available satellites. The first satellites of the Landsat family were equipped with the Multispectral Scanner (MSS), having four bands at 80-m resolution. AVHRR (Advanced Very High Resolution Radiometer) has five bands in 1.1-km resolution and has been flown on many platforms, including TIROS-N (Television Infrared Observation System). Later Landsat satellites had the Thematic Mapper (TM) sensors onboard with improved resolution and more spectral bands. The Indian Remote Sensing Satellites (IRS) 1A and 1B have two sensors called LISS-1 and LISS-2 (Linear Imaging and Self-Scanning Sensor), which are identical except for a two times higher spatial resolution on LISS-2. IRS 1C and 1D also have an identical payload being a 5.8-m resolution panchromatic camera (PAN) and a 23.5-m resolution multispectral sensor called LISS-3.

TABLE 1 SPECIFICATIONS OF IRS-P6 RESOURCESAT (COURTESY: EUROMAP.DE)

		LISS-IV		
		Mono Mode	MX Mode	LISS-II
Spatial Resolution	Band 2 (green)	5.8 m		23.5 m
	Band 3 (red)		5.8 m	23.5 m
	Band 4 (NIR)		5.8 m	23.5 m
	Band 5 (SWIR)		5.8 m	23.5 m

Proposed Methodology

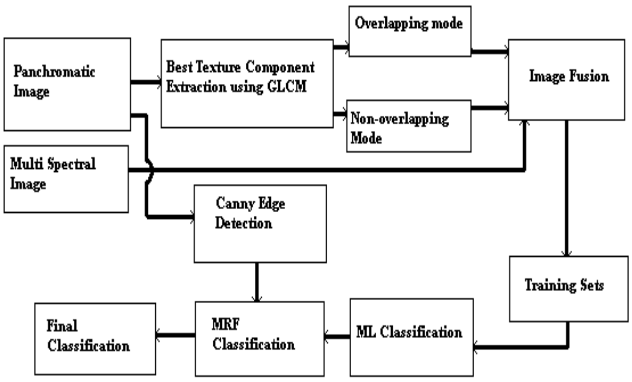


FIG.1 SCHEMATIC BLOCK DIAGRAM FOR PROPOSED METHODOLOGY OF IMAGE CLASSIFICATION

High resolution panchromatic remote sensing image scaled and cropped is given as input to the Gray Level Co-occurrence Matrix (GLCM) calculation module, the window size is also specified as input for both overlapping and non-overlapping mode. The GLCM is computed for the 5 textural elements homogeneity, contrast, entropy, energy and dissimilarity. The procedure is repeated till all the Texture elements for full image are calculated. Then texture features of the image are taken in form of texture image and the fusion has been performed on the texture image with the corresponding multi spectral image using 2-Broovey method. The fused image is given as input to Maximum Likelihood (ML) classifier, for which training classes are provided. The output is a classified image (image containing different Class regions). On the panchromatic image, the edge detector (Canny) is applied and the edges of the image (binary image) are obtained. The final classified image is obtained by passing binary image containing the edges and ML classified image into Markovian Random Field (MRF) classifier. The above approach results in extraction of single feature with higher accuracy as the textural, spectral and contextual data are considered.

GLCM Calculation and Texture Extraction

The texture spectrum, a statistical way to describe texture feature of an image, was first conceived by Wang. In this method a texture unit represents the local texture information for a given pixel and its neighborhood, and the global texture of an image is characterized with its texture spectrum. A texture image is represented as a set of essential small units termed as texture units which characterize the local texture information for a given pixel and its neighborhood. The statistics of all the texture units over the entire image reveal the global texture aspects.

To extract the texture features of panchromatic image window size and the mode of operations (Overlapping and Non-Overlapping) are to be given. The GLCM Matrix is calculated on the window of pixels and the texture value extracted is stored as a separate Array. This procedure is repeated by moving the window based on the mode of operation till the end of the panchromatic image and output is texture image. By following this procedure the five texture components Homogeneity, Contrast, Entropy, Dissimilarity, and Energy are computed. Spatial gray level co-occurrence estimates image properties related to second-order statistics. Gray level co-occurrence matrices (GLCM) which have become one of the most well-known and widely used texture features are utilized. The G*G gray level co-occurrence matrix Pd for a displacement vector d=(dx,dy) is defined as follows. The entry (i,j) of Pd is the number of occurrences of the pair of gray levels i and j which are a distance d apart. Formally, it is given as

$$P_d(i,j) = |\{((r,s),(t,v)) : I(r,s) = i, I(t,v) = j\}| \quad 3.1$$

where (r,s),(t,v) Є N*N , (t,v)=(r+dx,s+dy) and |.| is the cardinality of the set.

Autocorrelation Features

An important property of many textures is the repetitive nature of the placement of texture elements in the image. The autocorrelation function of an image is used to assess the amount of regularity as well as the fineness/coarseness of the texture present in the image. Formally, the autocorrelation function of an image I(x,y) is defined as follows:

$$\varrho(x,y) = \frac{\sum_{u=0}^{N}\sum_{v=0}^{N} I(u,v)I(u+x,v+y)}{\sum_{u=0}^{N}\sum_{v=0}^{N} I^2(u,v)} \quad 3.1.1$$

Special care needs to be taken while handling image boundaries. This function is related to the size of the texture primitive (i.e., the texture fineness). If the texture is coarse, then the autocorrelation equation (3.1.1) will drop off slowly; otherwise, it will drop off

very rapidly. The autocorrelation function provides peaks and valleys for regular textures and it is related to the power spectrum of the Fourier transform. Consider the image function in the spatial domain I(x,y) and its Fourier transform F(u,v). The quantity |F(u,v)|2 is defined as the power spectrum where |.| is the modulus of a complex number. This illustrates the effect of the directionality of a texture on the distribution of energy in the power spectrum.

TABLE 2 TEXTURE FEATURES THAT CAN BE EXTRACTED FROM GREY LEVEL CO-OCCURRENCE MATRICES

Texture Feature	Formula
Energy	$\sum_{i}\sum_{j}\mathbf{P_d^2(i,j)}$
Entropy	$-\sum_{i}\sum_{j}\mathbf{P_d(i,j)logP_d(i,j)}$
Contrast	$\sum_{i}\sum_{j}\mathbf{(i-j)^2P_d(i,j)}$
Homogeneity	$\sum_{i}\sum_{j}\frac{\mathbf{P_d(i,j)}}{\mathbf{1+\lvert i-j\rvert}}$
Correlation	$\frac{\sum_i\sum_j\mathbf{(i-\mu_x)(j-\mu_y)P_d(i,j)}}{\boldsymbol{\sigma_x\sigma_y}}$

Fusion under 2-Broovey Method

Standard method is used to fuse images (Panchromatic and the corresponding spectral image). The fused *R, G, B* bands are as follows

$$R_{new} = \frac{R}{R+G+B} * PAN$$

$$G_{new} = \frac{G}{R+G+B} * PAN$$

$$B_{new} = \frac{B}{R+G+B} * PAN$$

Here PAN refers to the calculated texture image. To apply the Broovey method, initially the principle components of the multispectral image (band1, band2, band3 or R, G, B) is computed and the first principle component which contains the maximum information of the image is substituted with the panchromatic image and the *R, G, B* values are recomputed using the above mentioned formula. This is the overlapping mode, where as in the non-overlapping mode the same PAN value is used for the entire window to which the value belongs. Thus, for all the spectral values in the window in the corresponding multispectral image, the same pan value for that window is applied. The resultant image is the fused image which is given to the next module as input.

ML Classification

The main aim of this module is to classify the fused image using the Maximum Likelihood Classifier. As this algorithm is supervised, the number of classes involved in the image and the training set for each of the classes is provided. The probability for a pixel belonging to a particular class is calculated and the same is repeated for all the classes and the pixel is assigned with a class which has the maximum probability. This is done till all the pixels in the image are classified.

Baye's Classification

Let the spectral classes for an image be represented by *wi* , *i*=1,2,……*M* where *M* is the total number of classes. In trying to determine the class or category to which a pixel vector *x* belongs, it strict in the conditional obabilities that are of interest. The measurement vector *x*, a column of brightness values for the pixel, describes the pixel as a point in multispectral space with co-ordinates defined by the brightness.

$$P(w_i|x), i = 1, \ldots.. M$$

The probability *P(ωi |x*) gives the likelihood that the correct class is *ωi* for a pixel at position *x*. Classification is performed according to equation 4.3.

$$x \in w_i, \text{if } p(w_i|x) > p(w_i|x) \text{for all } j = i$$

i.e., the pixel at *x* belongs to class *ωi* if *p(ωi |x)* is the largest. This intuitive decision rule is a special case of a more general rule in which the decisions are biased according to different degrees of significance being attached to different incorrect classifications. The general approach is called Bayes' classification.

Edge Detection

To detect the edges in the panchromatic image, have used Edge Canny method and the output of this module is binary image containing the edges in the original image.

Markovian Random Field Classification

The MRF Classification inputs are the ML Classified image and the binary image containing the edges. The probability of a pixel belonginga particular class is calculated using MRF with Line process making use of the Edges and the same is repeated for all the classes in addition, the pixel is assigned with a class which has the maximum probability. The output is the classified image. The effect of spatial context can also be incorporated into a classification using the concept of

the Markov Random Field (MRF). The Markov Random Field approach considers the whole image, rather than just a local neighborhood in the classification process. Supposed that there is a total of *M* pixels in the image to be classified with measurement vectors *x1, . . . xM*. Alternatively, the measurement vectors are expressed $\{xm : m = 1, \ldots M\}$, in which $m \equiv (i, j)$ in our usual way of indexing the pixels in an image. We can describe the full set of measurement vectors by $X = \{x1, \ldots xM\}$.

$$g_{cm}(x_m) = -\frac{1}{2}\ln|\Sigma_c| - \frac{1}{2}(x_m - m_c)\Sigma_c^{-1}(x_m - m_c)^t - \sum_{\partial m}\beta[1 - \delta(\omega_{cm}, \omega_{\partial m})] \quad (3.4.1)$$

It is recalled that classification is carried out on the basis of finding the class for the pixel that maximizes the discriminant function. It is noted from the above negative signs that the most appropriate class for pixel *m* is found by minimizing the expression:

$$d_{cm}(x_m) = \frac{1}{2}\ln|\Sigma_c| + \frac{1}{2}(x_m - m_c)\Sigma_c^{-1}(x_m - m_c)^t + \sum_{\partial m}\beta[1\delta(\omega_{cm}, \omega_{\partial m})] \quad (3.4.2)$$

To use (3.4.2) there needs to be an allocation of classes over the scene before the last term is computed. Accordingly, an initial classification would be performed with the maximum likelihood classifier and the Equation (3.4.1) would then be used to modify the labels attached to the individual pixels to incorporate the effect of context. However, if doing so some (or initially many) of the labels on the pixels will be modified. The process should then be run again and indeed as many times presumably until there are no further changes.

Results and Disscussion

The panchromatic image of the study area and highlighted parts of the image which are the areas of interest are shown in FIG. 2. Then the window size smaller than the object of interest in both modes i.e. overlapped and non-overlapped is specified.

The five textural filters have been processed on the panchromatic image. Different outputs for different features of GLCM have been taken in both the modes. FIG. 3a, an output of dissimilarity texture in over lapping mode, shows the local variation in the image. Thus, the area highlighted in the red contains the high intensity values which mean that there is a random gray levels attributed to the change in the regions (one region belonging to one class and the other region belonging to other). While theregion highlighted in the white contains the low intensity values which mean that there is a uniform gray level distribution.

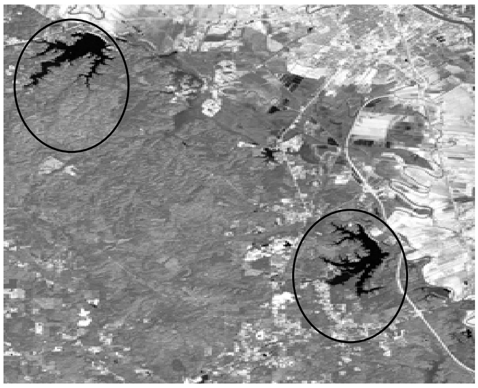


FIG. 2 PANCHROMATIC IMAGE

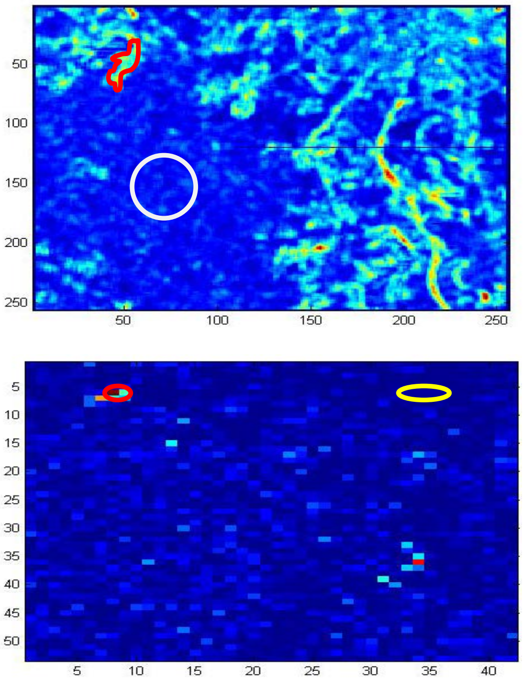


FIG. 3a AND 3b TEXTURE IMAGE OUTPUT OF THE DISSIMILARITY, ENERGY IN OVERLAPPING MODE AND NON-OVERLAPPING MODE

FIG. 3b shows the energy texture image of the input in non-overlapping mode in which window is moved by pixels equivalent to size of the window.

Energy measures textural uniformity is pixel pair repetitions. The area highlighted in the red contains high intensity values, therefore the window over which the value was obtained had a periodic or constant gray level distribution because high energy values occur when the gray level distribution over the window has either a constant or a periodic form. The area highlighted in the yellow contains low intensity values which mean that the window over which was calculated had a random gray level distribution. The

texture components of homogeneity and dissimilarity in overlapping mode fused with the multi spectral image FIG. 4 corresponding to the panchromatic image FIG. 2 are used for ML classification along with the training sets for the specified classes. The probability for a pixel to belonging to a particular class is calculated and the same is repeated for all the classes and the pixel is assigned with a class which has the maximum probability. This is done till all the pixels in the image are classified.

FIG. 4 MULTI SPECTRAL IMAGE

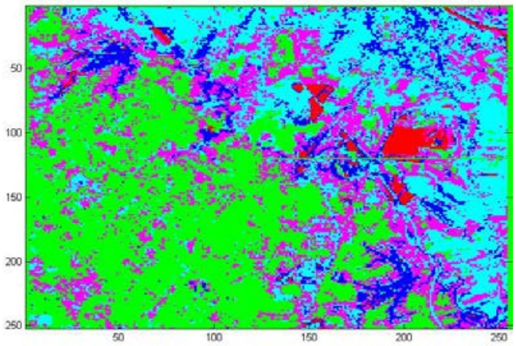


FIG. 5 ML CLASSIFICATION

The FIG. 5 is the output of the ML Classification which is classified based on the training data. The blue color part of the image is the object of interest (Water). The output has noise (the other parts of the image are also classified as water). The other regions include grass land (green), urban (cyan), field (red) and rest in pink. This is given to MRF to enhance the classification as well as to increase the accuracy. The FIG. 6 is output binary image after applying Canny Edge detection algorithm to detect the edges. ML classified image in FIG. 5 and binary image with edges are given as input for MRF classification specifying the number of iterations for classification.

The pobability for a pixel belonging to a particular class is calculated using MRF with Line process making use of the edges and the same is repeated for all the classes and the pixel is assigned with a class which has the maximum probability. The output is the classified image in which the water bodies are highlighted in blue.

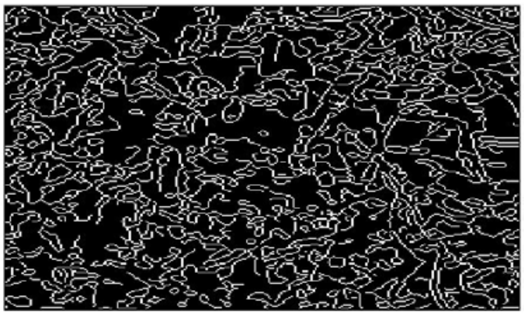


FIG. 6 BINARY IMAGES WITH EDGES OF THE PANCHROMATIC IMAGE

The desired result is an image with highlighted water bodies. Depending on the mode of operation, the texture features have been extracted. The image shown in the FIG. 7 is the final result obtained in Non Overlapping mode. The regions which are highlighted in blue are the water bodies. The advantage of using this mode to operate or this case is that it is the fastest and easiest way in identification of water bodies in the Remote Sense data but the accuracy is less compared to the Overlapping mode. The highlighted areas show the required water bodies. By visual interpretation and comparing with the desired result, it is found that the final result contains some noise ie., the other parts of the image are identified as water which are actually not.

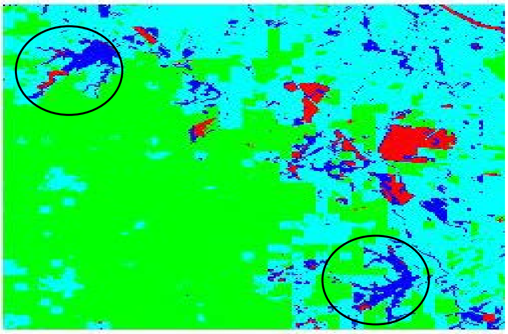


FIG. 7 FINAL RESULT IN NON OVERLAPPING MODE

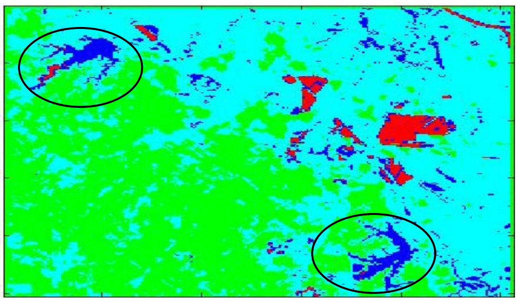
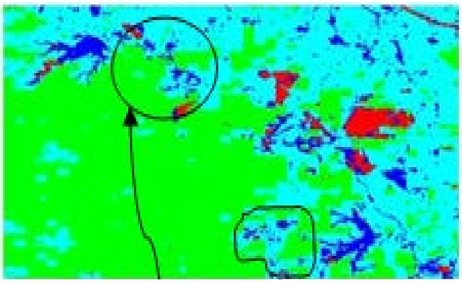
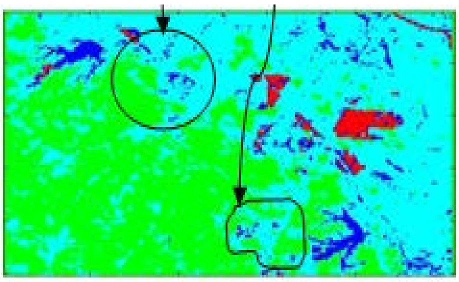


FIG. 8 FINAL RESULT IN OVERLAPPING MODE

The image shown in FIG. 8 is the final result which is obtained during the identification of water bodies' process using the Overlapping mode of operation. The accuracy of Overlapping mode in identification of water bodies is well comparatively with the Non Overlapping mode. The disadvantage in this mode of operation is that it takes more time than the Non Overlapping mode. Though the final result in this mode of operation differs from the desired result, the main aim of the project in the water bodies are identified along with some noise.The regions which are highlighted in blue are the water bodies. The highlighted areas show the required water bodies. By visual Interpretation and comparing with the desired result, it can be mentioned that the water bodies which are to be identified are identified along with some noise i.e. some parts of the image i are classified as water though they are not.

Conclusions





FIGS. 9a And 9b SHOW THAT THE NOISE LEVEL IN THE OVERLAPPING MODE IS LESS WHEN COMPARED TO THE NON-OVERLAPPING MODE I.E., THE ACCURACY LEVEL IN CLASSIFICATION OF THE IMAGE IS MORE IN THE OVERLAPPING MODE THAN IN THE NON OVERLAPPING MODE.

Final results which are obtained in non-overlapping and overlapping mode are shown in the FIG. 9a and FIG. 9b respectively. The highlighted parts in blue are the water bodies which are identified. Each has its own advantages as well as disadvantages. Though images are seen to be the same by visual interpretation both in the non-overlapping mode which is the fastest and the overlapping mode which is the slowest the accuracy level in identification of water bodies in the Remote Sensing data is higher in overlapping mode than that in the Non Overlapping mode. Survey on water bodies which can be effectively used for drinking water supply, depleted can be detected with ease and the exact area can be identified for marking purpose. Even this is extensively useful in identifying legal and illegal fisheries in the selected region without inspecting them in person. It is obvious that this improves the standard survey by automating the whole process.

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